Intergenerational Transmission of Inequality: Maternal Endowments, Investments, and Birth Outcomes

APPENDIX

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Contents

A Detailed Results

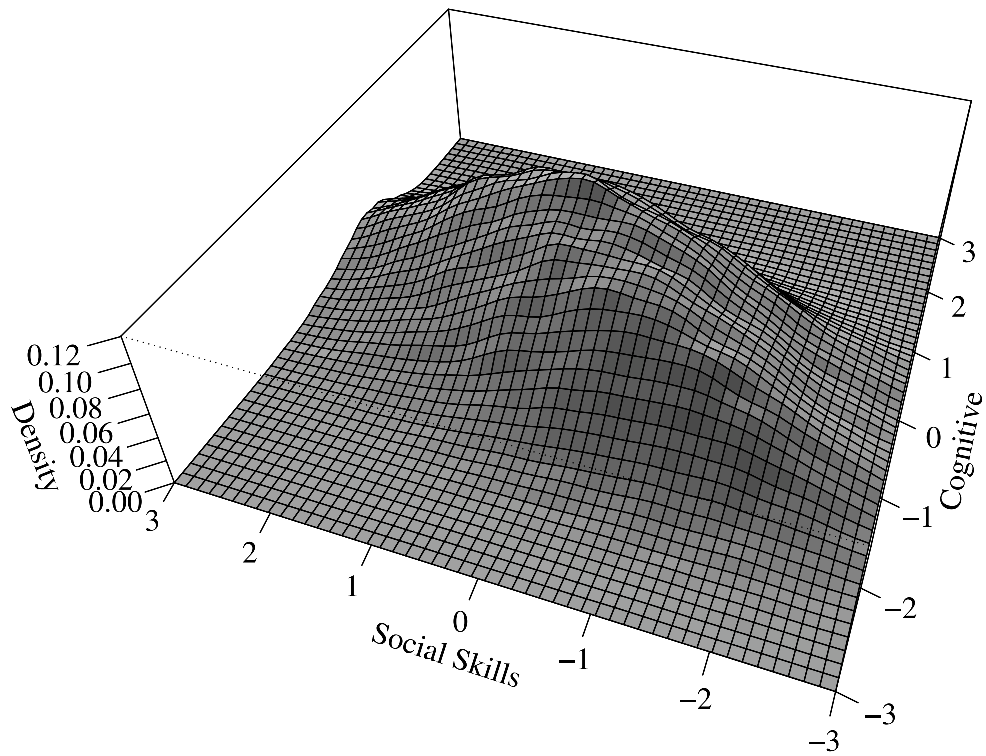
This Appendix shows an extended version of Tables 4 and 6 which includes the estimated coefficients on all the covariates.

Table A.1: Full model results (outcome system)

	Education	Smoking ($E=1$)	Smoking ($E=0$)	$SGA(E=1,S=1)$	$SGA(E=0,S=1)$	$SGA(E=1,S=0)$	$SGA(E=0,S=0)$
Cognitive	14.677	-0.616	-0.297	-0.23	1.042	0.153	-1.276
se	(1)	(1)	(1)	(1)	(1)	(1)	(1)
Social	3.727	-3.361	-4.364	0.641	-0.999	-0.803	0.572
se	(1)	(1)	(1)	(1)	(1)	(1)	(1)
Physical constitution	1.271	0.075	0.901	-1.51	-4.083	-2.593	-3.501
se	(1)	(1)	(1)	(1)	(1)	(1)	(1)
Constant	-1.917	-3.061	-1.987	-1.779	-0.907	-1.188	-1.164
se	(0.206)	(0.825)	(0.381)	(1.047)	(0.128)	(0.147)	(0.078)
Child sex (female)				0.07	0.14	0.077	0.111
se				(0.714)	(0.139)	(0.142)	(0.094)
Mother first born	0.439	-0.209	-0.3				
se	(0.062)	(0.157)	(0.077)				
Scotland(age16)	0.541	0.255	0.115	0.739	-0.104	-0.503	-0.119
se	(0.119)	(0.203)	(0.114)	(0.812)	(0.2)	(0.288)	(0.173)
London(age16)	0.069	0.249	-0.125	0.222	-0.061	-0.082	-0.262
se	(0.101)	(0.225)	(0.133)	(1.182)	(0.29)	(0.264)	(0.18)
Wales(age16)	0.398	-0.053	0.135	0.763	0.107	-0.015	-0.186
se	(0.115)	(0.264)	(0.141)	(1.487)	(0.268)	(0.264)	(0.243)
% Smoking in Region		6.572	5.704				
se		(1.952)	(0.919)				
Change in unemployment rate	0.153						
se	(0.098)						
Grandmother smokes		0.008	0.163				
se		(0.148)	(0.072)				
Grandmother Post-Compulsory Education	0.653	-0.43	-0.025	0.573	0.135	-0.183	-0.08
se	(0.064)	(0.16)	(0.094)	(0.748)	(0.18)	(0.148)	(0.125)
Grandparental SES High	0.945	-0.098	-0.559				
se	(0.09)	(0.235)	(0.141)				
Grandparental SES Medium	0.406	-0.021	-0.292				
se	(0.071)	(0.198)	(0.072)				
Grandmother Age at Birth of Mother	0.026	-0.002	-0.01				
se	(0.005)	(0.014)	(0.007)				

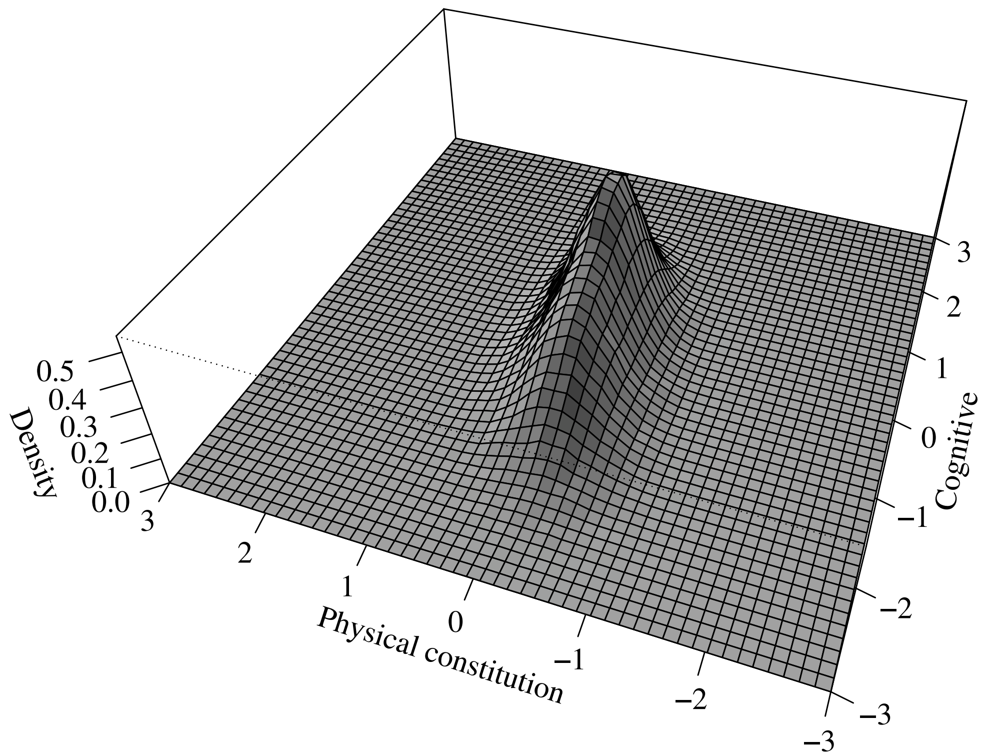
B Factor Distributions

Figure B.1: Joint distribution of cognitive and social skills



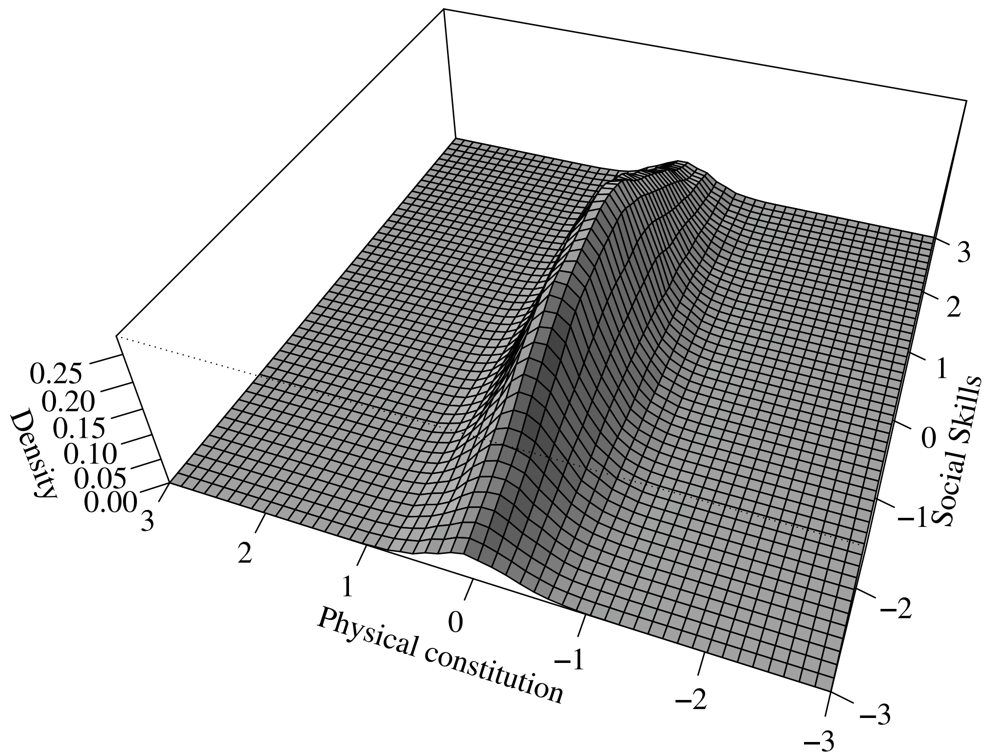
Note: National Child Development Study (NCDS), Birth cohort 1958. The analytical sample on which these estimates are based consists of all female cohort members that have no missings in any of the covariates. **Notes:** Joint mixture distribution of traits.

Figure B.3: Joint distribution of cognitive skills and physical constitution



Note: National Child Development Study (NCDS), Birth cohort 1958. The analytical sample on which these estimates are based consists of all female cohort members that have no missings in any of the covariates. **Notes:** Joint mixture distribution of traits.

Figure B.5: Joint distribution of social skills and physical contitution



Note: National Child Development Study (NCDS), Birth cohort 1958. The analytical sample on which these estimates are based consists of all female cohort members that have no missings in any of the covariates. **Notes:** Joint mixture distribution of traits.

C Robustness tests

C.1 Using low birth weight instead of small for gestational age as measure of newborn health

As already mentioned in Section 4.2, size at birth reflects two factors: gestational length and the rate of fetal growth. Hence, if birth weight or low birth weight (less than 2,500 grams at birth) are used as indicators of fetal health as manifested at birth, this leads to confounding effects of growth and maturity. Hence, we use SGA as our main outcome. However, in order to make our results comparable to much of the previous literature, we have re-estimated all our models using low birth weight as an outcome. In our sample, the prevalence of low birth weight is around 7%, therefore lower than the prevalence of SGA. Around 90% of babies who are normal weight are also categorized as normal size for gestational age. However, only a little more than 50% of the babies who are low birth weight are also SGA.

What we learn from this robustness exercise is that, while using LBW as an outcome leaves the main qualitative results unchanged, it does lead to differences in the impact of maternal physical constitution, in the size of the treatment effect of smoking and in the heterogeneity results. We have already discussed these results in the paper in the different sections where relevant, and we present all of them here now for completeness.

First, Table C.1 reports the results on the effects of maternal traits on her choices and newborn outcomes (the corresponding SGA Table is 6): we notice that, while the effects of the cognitive and social skills are very similar (both quantitatively and qualitatively) to those obtained when using SGA as outcome, the physical constitution of the mother is not a significant determinant of the probability of delivering a low birth weight baby, after conditioning on the education and smoking choices. We then examine the total impact of maternal traits on newborn outcomes: Figure C.1 shows that the biggest difference with respect to the SGA results is in the effect of maternal physical constitution, while cognition has no effect on the probability of delivering a LBW baby, and social skills a very similar one to the one obtained when using SGA as an outcome. In particular, an early nutritional intervention which would move the mother from the 20^{th} to the 80^{th} percentile of the physical traits distribution would be associated with a reduction in the probability of delivering a LBW baby of only 3 pp, in contrast to the 10 pp obtained when using SGA as outcome (Figure 6).

We then decompose the channels through which maternal traits affect LBW, and we report the results in Figure C.2. As compared to the results obtained using SGA (Figure 7), we find a significant residual effect of both cognition and social skills on low birth weight. The lack of biological plausibility of these results reassures us again about our choice of SGA as the main outcome as more genuinely capturing the rate of fetal growth.

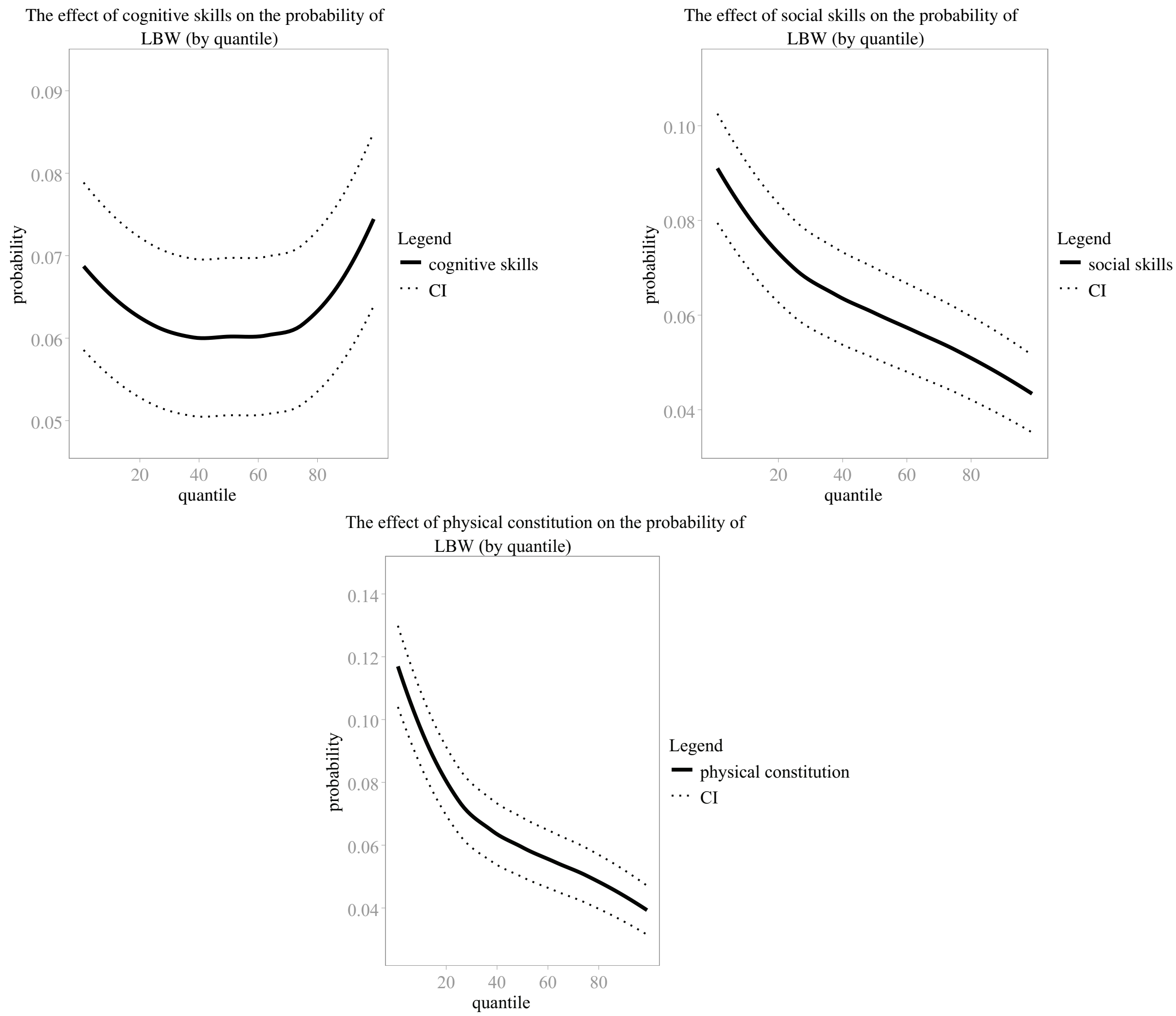
We finally compute the treatment effect of education and smoking on the probability of delivering a LBW baby (Table C.2), and we investigate the presence of heterogeneous effects (Table C.3). While the treatment effects of education are comparable to those obtained when using SGA as outcome, we find that smoking increases the probability of delivering a LBW baby by around 5pp, which is half of the effect found for SGA (Table 10). Lastly, the heterogeneity results reveal that the effect of education on the probability of delivering a LBW baby is significantly higher at the bottom of the cognitive and social skills distribution, while it has basically no impact at the top (instead, we found homogeneity in the effects of maternal education along the cognitive and social skills distributions when using SGA as outcome, see Figure 9); comparable to those obtained when using SGA as an outcome are, instead, the treatment effects of smoking on LBW along the distribution of maternal traits (see again Figure 9).

Table C.1: Average marginal effects of a one standard deviation change in maternal traits

	Cognitive Skills	Social Skills	Physical Constitution
Education	0.153	0.039	0.015
	(0.045)	(0.015)	(0.013)
Smoking(E=1)	-0.012	-0.061	0.003
	(0.022)	(0.038)	(0.026)
Smoking(E=0)	-0.003	-0.056	0.011
	(0.013)	(0.021)	(0.015)
LBW(E=1, S=1)	0.07	-0.005	-0.056
	(0.163)	(0.074)	(0.164)
LBW(E=0, S=1)	0.003	-0.007	-0.039
	(0.017)	(0.017)	(0.026)
LBW(E=1, S=0)	0.01	-0.004	-0.008
	(0.015)	(0.012)	(0.015)
LBW(E=0, S=0)	-0.003	-0.011	-0.007
	(0.009)	(0.009)	(0.01)

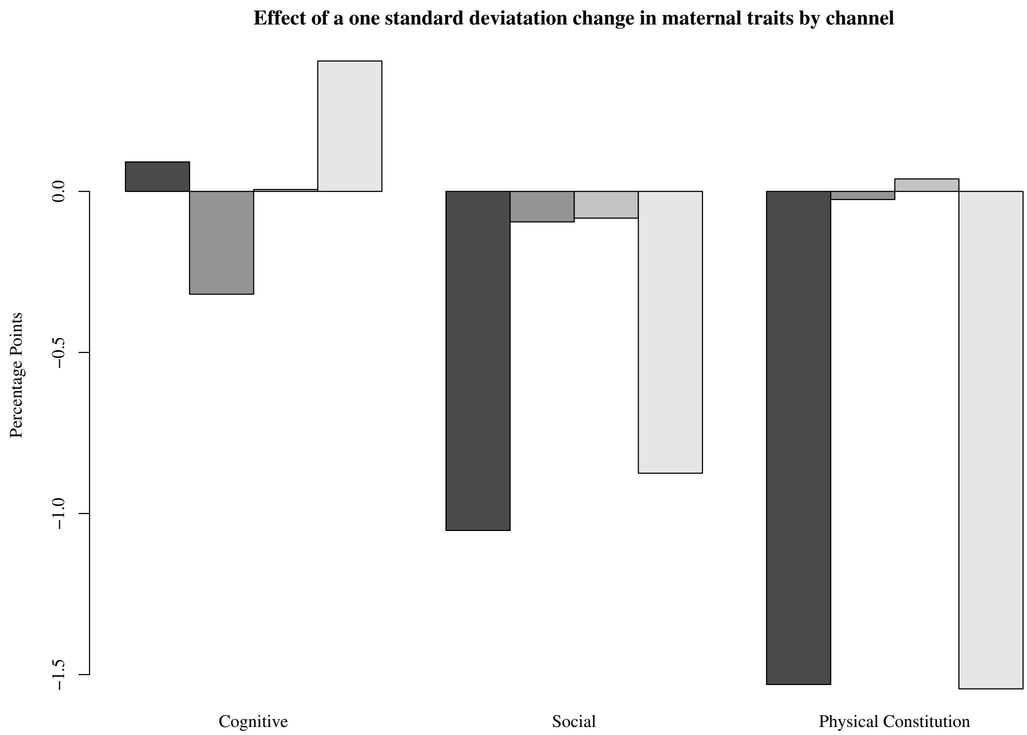
Note: National Child Development Study (NCDS), Birth cohort 1958. The analytical sample on which these estimates are based consists of all female cohort members that have no missings in any of the covariates. Standard errors in brackets. E=education; S=smoking; LBW=low birth weight.

Figure C.1: Effect of maternal traits on newborn LBW



Note: National Child Development Study (NCDS), Birth cohort 1958. The analytical sample on which these estimates are based consists of all female cohort members that have no missings in any of the covariates. When computing the overall effect of each trait in turn on the probability of delivering a LBW newborn, the other two traits are fixed at their respective means.

Figure C.2: Decomposing the effects of maternal endowments on newborn LBW



Note: National Child Development Study (NCDS), Birth cohort 1958. The analytical sample on which these estimates are based consists of all female cohort members that have no missings in any of the covariates. The length of the bar "Total" shows the overall reduction in the probability of delivering a LBW baby which is associated with a one standard deviation increase in each of the three maternal endowments. The respective contributions of the various channels are shown in the bars "education", "smoking" and "residual", respectively.

Table C.2: Treatment effect of smoking and education

Treatment effect of	ATE	ATT	ATNT	AMTE
education on smoking in pregnancy	-0.096	-0.092	-0.098	-0.097
	(0.01)	(0.009)	(0.01)	(0.01)
education on the probability of	-0.008	-0.002	-0.011	-0.009
delivering a LBW baby	(0.006)	(0.006)	(0.006)	(0.006)
smoking on the probability of	0.051	0.052	0.051	0.052
delivering a LBW baby	(0.007)	(0.007)	(0.007)	(0.007)

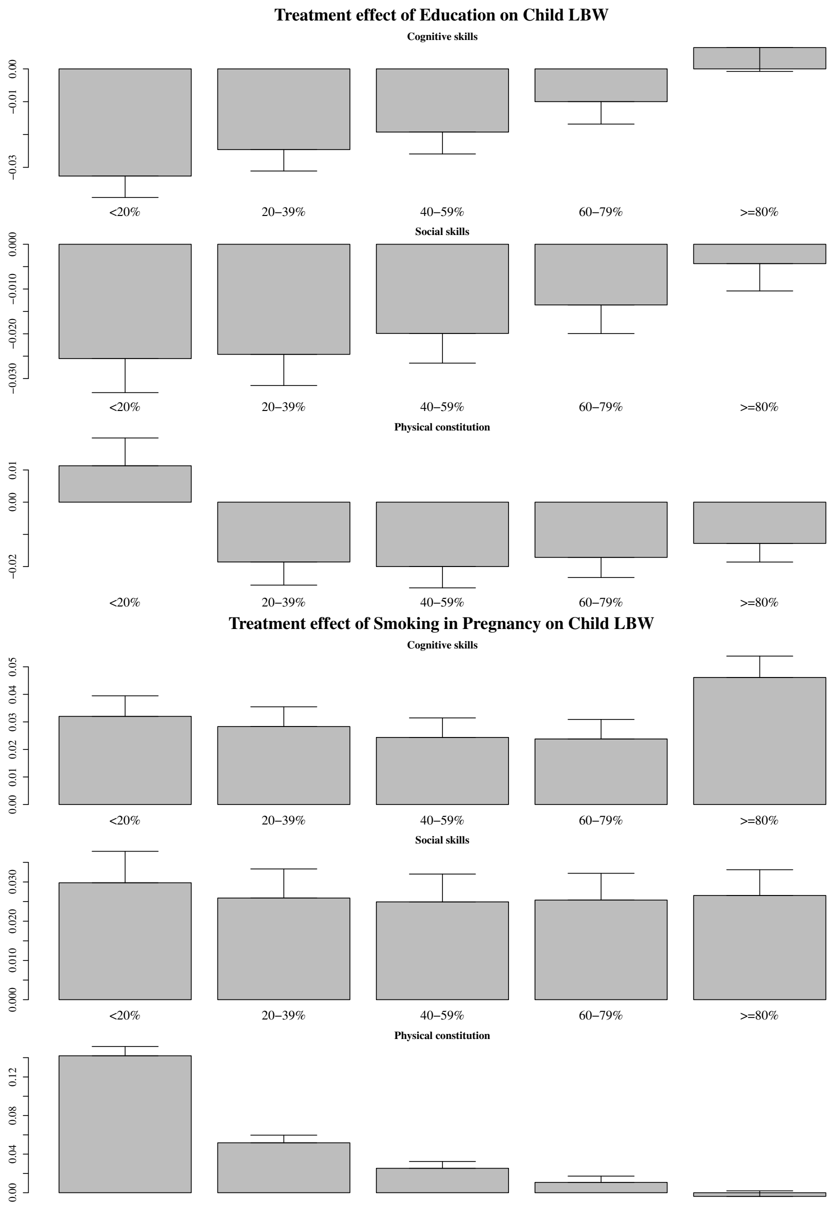
Note: National Child Development Study (NCDS), Birth cohort 1958. The analytical sample on which these estimates are based consists of all female cohort members that have no missings in any of the covariates. The numbers in columns 2-5 are the treatment effects, as specified: ATE=Average Treatment Effect; ATT=Average Treatment Effect on the Treated; ATNT=Average Treatment Effect on the Non-Treated; AMTE=Average Marginal Treatment Effect. Standard errors in brackets.

Table C.3: Decomposition of the effects of maternal endowments on newborn LBW

	Cognitive Skills	Social Skills	Body Size
Education	354	9	2
Smoking	-10	8	-2.5
Factor residual	-444	83	100.5
TOTAL	100	100	100

Note: Numbers in cell show the percentage of the overall effect of each maternal trait which works through the education and smoking choices, and the residual effect. National Child Development Study (NCDS), Birth cohort 1958. The analytical sample on which these estimates are based consists of all female cohort members that have no missings in any of the covariates.

Figure C.3: Heterogenous treatment effects of education and smoking on LBW along the distribution of maternal traits



Note: National Child Development Study (NCDS), Birth cohort 1958. The analytical sample on which these estimates are based consists of all female cohort members that have no missings in any of the covariates. Whiskers display standard errors.

C.2 Restricting sample to full term deliveries

As mentioned in Section 4.2, our main outcome of interest SGA (Small for Gestational Age) can be measured with error. There are two main reasons: 1) the variable is based on the recall of the last menstrual period (LMP) and 2) the charts for SGA are constructed based on the distribution of live birth at any point in gestation. The problem related with the first source of measurement error is minimized for full term deliveries. The intuition is simply that the lesser the expected date (as based on the LMP) and the actual date coincide, the higher the probability that the expected date was wrong. In fact, for deliveries in the 37-41 weeks range, up to 96% of them happen within one week of the expected date (Strauss (2000), Poulsen et al. (2011), Wingate et al. (2007), Kramer et al. (1988), Mustafa and David (2001)). The second problem leads to consistent underestimation of SGA infants in early deliveries, because SGA is defined as being below the 10% of the distribution of birth weight by gestation for live births. Yet, most healthy infants will not be born premature, so problem 2) is comparable to a missing data problem (Hutcheon and Platt, 2008) and would also be minimized by restricting the sample to deliveries in the 37-41 weeks range. Hence, restricting the sample to full term births would minimize the problems discussed above, but at the same time would have the important drawback of loosing important variation from the data, by discarding all the premature births.

While the results in the paper are based on a sample which includes all gestational ages, in this appendix we have also re-estimated all the models by restricting the sample to full-term deliveries. As shown in Tables C.4[1] and C.5,[2] the results are comparable. This suggests that the presence of measurement error in SGA does not constitute a serious issue in our data.[3]

[1]This corresponds to Table 6 in the main text.

[2]This corresponds to Table 10 in the main text.

[3]We thank Heather Royer for suggesting us to perform this robustness test.

C.3 Using different references for birth weight by gestation

The last robustness test that we perform refers to the use of a difference reference chart, since there is no one unique chart for birth weight by gestational age that is unanimously recognized as the gold standard. We have chosen the one most commonly adopted in the literature: the Babson and Benda's chart, as updated by Fenton. This is also the table featured in standard Neonatology manuals in the USA (e.g, see Gomella et al. (1999)). Another common chart recommended for the USA is the one proposed in Alexander et al. (1996). There exists a debate on whether charts should be population specific or if instead there should be one, universal chart. The latter approach has been adopted for children, in which case the WHO growth charts are recognized as the standard. Charts for fetal growth, instead, tend to be population specific and even tailored to maternal characteristics (Gardosi, 2006), because of the well-known impact of maternal physical constitution on newborn weight.[4]

Importantly, the difference between the USA and the UK reference charts is minimal. Nonetheless, in order to provide one more check of the robustness of our results, we have also re-estimated all the models using the latest birth weight by gestational age charts for Great Britain, which are constructed on the basis of births from Scotland (Bonellie et al., 2008), and are the latest tables adopted in official publications.[5]

As expected, the results, reported in Tables C.6 and C.7, are very similar to those obtained by using the US charts – which reassures us once more of the robustness of our findings.

[4]Notice we do not need to use a "tailored" growth chart since we explicitly include maternal physical constitution in our model.

[5]The classical UK reference chart is outdated (Thomson et al., 1968), and these are constructed on the basis of a much bigger number of births than the original ones.

Table C.4: Average marginal effects of a one standard deviation change in maternal traits

	Cognitive Skills	Social Skills	Physical Constitution
Education	0.156	0.038	0.017
	(0.045)	(0.015)	(0.015)
Smoking(E=1)	-0.024	-0.069	0.001
	(0.026)	(0.044)	(0.032)
Smoking(E=0)	-0.009	-0.059	0.029
	(0.015)	(0.024)	(0.02)
SGA(E=1, S=1)	0.009	0.11	-0.17
	(0.121)	(0.173)	(0.253)
SGA(E=0, S=1)	0.02	-0.012	-0.097
	(0.031)	(0.028)	(0.049)
SGA(E=1, S=0)	-0.001	-0.028	-0.061
	(0.024)	(0.025)	(0.056)
SGA(E=0, S=0)	-0.018	0.004	-0.044
	(0.014)	(0.016)	(0.022)

Note: National Child Development Study (NCDS), Birth cohort 1958. The analytical sample on which these estimates are based consists of all female cohort members that have no missings in any of the covariates. Standard errors in brackets. E=education; S=smoking; SGA=small for gestational age. Sample is restricted to full-term babies (37-41 weeks of gestation).

Table C.5: Treatment effect of smoking and education

	Observed Difference	ATE	Sorting Gain	Bias
EDU on SMOKING in Pregnancy	-0.154	-0.079	-0.007	-0.068
EDU on SGA probability	-0.049	-0.004	-0.012	-0.033
SMOKING on SGA probability	0.097	0.118	-0.024	0.003

Note: National Child Development Study (NCDS), Birth cohort 1958. The analytical sample on which these estimates are based consists of all female cohort members that have no missings in any of the covariates. The numbers in columns 2-5 are the treatment effects, as specified: ATE=Average Treatment Effect; ATT=Average Treatment Effect on the Treated; ATNT=Average Treatment Effect on the Non-Treated; AMTE=Average Marginal Treatment Effect. Sample is restricted to full-term babies (37-41 weeks of gestation). Standard errors in brackets.

Table C.6: Average marginal effects of a one standard deviation change in maternal traits

	Cognitive Skills	Social Skills	Physical Constitution
Education	0.153	0.04	0.016
	(0.045)	(0.014)	(0.013)
Smoking(E=1)	-0.012	-0.062	0.001
	(0.023)	(0.039)	(0.026)
Smoking(E=0)	-0.004	-0.055	0.013
	(0.012)	(0.021)	(0.016)
SGA(E=1, S=1)	-0.045	-0.004	-0.125
	(0.092)	(0.101)	(0.169)
SGA(E=0, S=1)	0.015	-0.022	-0.088
	(0.024)	(0.022)	(0.042)
SGA(E=1, S=0)	-0.005	0.005	-0.043
	(0.018)	(0.019)	(0.032)
SGA(E=0, S=0)	-0.015	0.006	-0.042
	(0.012)	(0.013)	(0.023)

Note: National Child Development Study (NCDS), Birth cohort 1958. The analytical sample on which these estimates are based consists of all female cohort members that have no missings in any of the covariates. Standard errors in brackets. E=education; S=smoking; SGA=small for gestational age. SGA is defined using Bonellie et al. (2008) table.

Table C.7: Treatment effect of smoking and education

	Observed Difference	ATE	Sorting Gain	Bias
EDU on SMOKING in Pregnancy	-0.166	-0.097	0.004	-0.072
EDU on SGA probability	-0.034	-0.002	-0.012	-0.020
SMOKING on SGA probability	0.104	0.104	0.001	-0.001

Note: National Child Development Study (NCDS), Birth cohort 1958. The analytical sample on which these estimates are based consists of all female cohort members that have no missings in any of the covariates. The numbers in columns 2-5 are the treatment effects, as specified: ATE=Average Treatment Effect; ATT=Average Treatment Effect on the Treated; ATNT=Average Treatment Effect on the Non-Treated; AMTE=Average Marginal Treatment Effect. Standard errors in brackets. SGA is defined using Bonellie et al. (2008) table.

D Three-Step Estimation Procedure

As mentioned in Section 3 we use Bayesian MCMC methods to estimate the parameters of our sequential selection model with a factor structure; however, we also present results from a stepwise procedure which uses factor scores as proxies for factors, similar to the one in Heckman et al. (2013). The advantage of using factors scores instead of a simple (unweighted) sum of measures is that the weights (loadings) are not required to be uniform across items, but instead reflect the estimated correlation between each item and the latent factor. We perform the following three steps. First, we estimate the parameters of the measurement system. Second, we predict factor scores for each individual, using the estimated parameters obtained in the first step. Third, we include these predicted scores as observed covariates in choice and outcome equations.

While this three-step approach avoids poor convergence, multiple local maxima, and instability of the model with respect to estimated parameters, as compared to full maximum likelihood estimation, the method produces biased coefficients in the outcome equations of the model. If not bias-corrected, coefficients are plagued by attenuation bias by a standard errors-in-variables argument (Croon, 2002). We correct for this bias following a procedure due to Iwata (1992), which is similar to the one described in Lu and Thomas (2008) and employed in Heckman et al. (2013). However, our method slightly differs from theirs, as we correct the factor scores before using them in the outcome system; additionally, our method has the advantage that it can also be applied to some nonlinear models, like the probit, which we use.

D.1 Factor Score Prediction

Here we detail the second step of our three-step estimation procedure. Let's start by assuming a linear relationship between the vector of measurements (M) and the vector of factors (Θ), so that the measurement system for agent i, $i \in \{1, \ldots, N\}$ can be written as:

$$M_{k,i} = \sum_{s=1}^{S} \lambda_{k,s}\theta_{s,i} + \epsilon_{k,i}, \quad \text{for} \quad k = 1, \ldots, K \quad \text{and} \quad s = 1, \ldots, S$$

or in matrix notation $M_i = \Lambda\Theta_i + \varepsilon_i$. Denote the covariance matrices of ε_i and M_i as $V[\varepsilon_i] = \Sigma$, and $V[M_i] = \Omega$. Furthermore, assume that $\theta_i \perp\!\!\!\perp \epsilon_{k,i}$ and that $\epsilon_{j,i} \perp\!\!\!\perp \epsilon_{k,i} \quad \forall \quad k \neq j$. Hence, ε_i are mutually independent uniquenesses that capture the stochastic measurement error component and Λ is a matrix of factor loadings. Furthermore, denote $E[\Theta\Theta'] = \Phi$ and assume $E[\Theta] = 0$ and $E[\varepsilon] = 0$ to set the location of the factors. Hence, the covariance matrix of the measurements can be written as $\Omega = \Lambda\Phi\Lambda' + \Sigma$. In practice, we assume that each factor loads on a distinct set of measurements (so-called "dedicated"), so that Λ is also distinct for each system of measurements. Furthermore, we set the scale of the factors by normalizing the factor loading of the first measurement equation for each factor equal to 1. Last, we set $K \geq 3$ for each factor to ensure identification.

After having estimated the covariance matrices and the parameters of the vector Λ in a first step, we now aim to estimate a vector of factor scores $\widehat{\Theta_i}$ that approximates the true vector of skills Θ_i for each individual i. We use Bartlett's estimator which is based on the minimization of the mean squared error (MSE) of the above equation, because of its desirable unbiasedness properties (Saris et al., 1978; Skrondal and Laake, 2001). Bartlett's factor scores are given by:

$$\widehat{\Theta_i}^{B'} = \left(\hat{\Lambda}'\hat{\Sigma}^{-1}\hat{\Lambda}\right)^{-1}\hat{\Lambda}'\hat{\Sigma}^{-1}M_i$$

Hence, Bartlett's estimator is a GLS procedure which provides the maximum likelihood estimates of $\widehat{\Theta_i}^{B'}$, conditional on the data M_i.[6]

D.2 Bias Correction

Finally, to correct for the attenuation bias that arises from using estimated instead of true factors, we use a simple estimation method proposed by Iwata (1992), which may be applied

[6]Notice that the data are used twice: first to obtain estimates of the factor loadings, then to predict the factor scores, treating the factor loadings as regressors.

to linear models as well as a certain class of nonlinear models. The idea is to replace the unobserved true vector of latent factors by some estimate and then to estimate the regression parameters in the usual way. Consider the following model:

$$Y_i = \Lambda\Theta_i^* + \varepsilon_i$$

where

$$\Theta_i^* = \Theta_i + V_i$$

where Θ_i is the measured Θ_i^*. Furthermore, it is assumed that $\Theta_i \perp\!\!\!\perp V_i$, $\mathrm{E}[V_i] = 0$ and that $(\Theta_i, \varepsilon_i)$ are iid. Denote the covariance matrix of Θ_i^* as $Cov(\Theta_i^*, \Theta_i^*) = \Sigma_{\Theta_i^*\Theta_i^*}$, the covariance matrix of V as $Cov(V,V) = \Omega$ and $\Sigma_{\Theta_i^*\Theta_i^*} = \Sigma_{\Theta_i\Theta_i} - \Omega$. A consistent estimator of $\Sigma_{\Theta_i\Theta_i}$ can be obtained when estimating the measurement system as explained in the previous section. If we used Θ_i instead of Θ_i^*, the OLS estimator denoted as $\mathbf{L} = (\Theta'\Theta)^{-1}\Theta'\mathbf{Y}$ would be inconsistent. However,

$$\Lambda = \left(\Sigma_{\Theta^*\Theta^*}\right)^{-1}\Sigma_{\Theta\Theta}\mathbf{L} \tag{1}$$

is consistent. Equation 1 can be rewritten as:

$$\begin{aligned}
\Lambda &= \left(\Sigma_{\Theta^*\Theta^*}\right)\Sigma_{\Theta\Theta}\left(\Theta'\Theta\right)^{-1}\Theta'\mathbf{Y} \\
\Lambda &= \left(\Sigma_{\Theta^*\Theta^*}\left(\Sigma_{\Theta\Theta}\right)^{-1}\Theta'\Theta\left(\Sigma_{\Theta\Theta}\right)^{-1}\Sigma_{\Theta^*\Theta^*}\right)^{-1}\Sigma_{\Theta^*\Theta^*}\left(\Sigma_{\Theta\Theta}\right)^{-1}\Theta'\mathbf{Y} \\
\Lambda &= \left(\hat{\Theta}'^*\hat{\Theta}^*\right)^{-1}\hat{\Theta}^{*\prime}\mathbf{Y},
\end{aligned}$$

where:

$$\hat{\Theta}^* = \Theta\left(\Sigma_{\Theta\Theta}\right)^{-1}\Sigma_{\Theta^*\Theta^*}.$$

Hence, $\hat{\Theta}^*$ is a consistent estimator of Θ^*. Furthermore, Iwata (1992) shows that this estimator retains consistency in certain classes of nonlinear models, such as the probit model.

References

Alexander, G., J. Himes, R. Kaufman, J. Mor, and M. Kogan (1996). A united states national reference for fetal growth. *Obstetrics & Gynecology 87*(2), 163–168.

Bonellie, S., J. Chalmers, R. Gray, I. Greer, S. Jarvis, and C. Williams (2008). Centile charts for birthweight for gestational age for Scottish singleton births. *BMC pregnancy and childbirth 8*(1), 5.

Croon, M. (2002). Using predicted latent scores in general latent structure models. *Latent variable and latent structure models, Chapter 10*, 195.

Gardosi, J. (2006). New definition of small for gestational age based on fetal growth potential. *Hormone Research in Paediatrics 65*(3), 15–18.

Gomella, T., M. Cunningham, F. Eyal, and K. Zenk (1999). *Neonatology: management, procedures, on-call problems, diseases, and drugs*. Appleton & Lange.

Heckman, J., R. Pinto, and P. Savelyev (2013). Understanding the mechanisms through which an influential early childhood program boosted adult outcomes. *American Economic Review 103*(6), 2052–2086.

Hutcheon, J. and R. Platt (2008). The missing data problem in birth weight percentiles and thresholds for small-for-gestational-age. *American journal of epidemiology 167*(7), 786–792.

Iwata, S. (1992). Errors-in-variables regression using estimated latent variables. *Econometric Reviews 11*(2), 195–200.

Kramer, M., F. McLean, M. Boyd, and R. Usher (1988). The validity of gestational age estimation by menstrual dating in term, preterm, and postterm gestations. *Journal of the American Medical Association 260*(22), 3306–3308.

Lu, I. and D. R. Thomas (2008). Avoiding and Correcting Bias in Score-Based Latent Variable Regression With Discrete Manifest Items. *Structural Equation Modeling: A Multidisciplinary Journal 15*(3), 462–490.

Mustafa, G. and R. David (2001). Comparative accuracy of clinical estimate versus menstrual gestational age in computerized birth certificates. *Public Health Reports 116*(1), 15.

Poulsen, G., J. Kurinczuk, D. Wolke, E. Boyle, D. Field, Z. Alfirevic, and M. Quigley (2011). Accurate reporting of expected delivery date by mothers 9 months after birth. *Journal of Clinical Epidemiology*, 1444–1450.

Saris, W., M. de Pijper, and J. Mulder (1978). Optimal procedures for estimation of factor scores. *Sociological Methods & Research 7*(1), 85.

Skrondal, A. and P. Laake (2001). Regression among factor scores. *Psychometrika 66*(4), 563–575.

Strauss, R. (2000). Adult Functional Outcome of Those Born Small for Gestational Age Twenty-six-Year Follow-up of the 1970 British Birth Cohort. *JAMA 283*(5), 625–632.

Thomson, A., W. Billewicz, and F. Hytten (1968). The assessment of fetal growth. *BJOG: An International Journal of Obstetrics & Gynaecology 75*(9), 903–916.

Wingate, M., G. Alexander, P. Buekens, and A. Vahratian (2007). Comparison of gestational age classifications: date of last menstrual period vs. clinical estimate. *Annals of epidemiology 17*(6), 425–430.